Potholes Recognition Model using Lightweight Faster Region-Convolutional Neural Network for Autonomous Car.

Rabiatu Kasim Ibrahim[1], Rabi Mustapha[2], Khalid Haruna[3],
Department of Computer Science, Kaduna State University, Kaduna, Nigeria
rakjere01@gmail.com

Abstract

Potholes pose a threat to driver safety and can lead to traffic accidents, emphasizing the need for efficient and proactive pothole management in complex road environments. This not only secures driver safety but also contributes to accident prevention and the smooth flow of traffic. This paper addresses the pothole detection challenge by employing an Enhanced Faster RCNN algorithm, which integrates Faster RCNN with EfficientNet. The focus is on improving detection performance, especially for autonomous cars in third-world countries like Nigeria. Using Lightweight Faster R-CNN with EfficientNet, the model exhibits outstanding performance and achieved an accuracy rate of 97.7%, surpassing other CNN architectures like MobileNet V3, ResNet 50, VGG16, and Inception V3. The results underscore the model's effectiveness for real-time decision-making in pothole detection, indicating its potential practical application in third-world countries, offering a valuable solution for safer and more efficient navigation on potholed roads.

Keywords: *Pothole detection, Accident Prevention, Autonomous Vehicle Systems (AVS), Lightweight Faster RCNN*

1. Introduction

The recent advancements in artificial intelligence have paved the way for the development of Autonomous Vehicle Systems (AVS) in the automotive industry. However, ensuring the safety of human lives in real road conditions remains a challenge for these industries. The World Health Organization has reported high road death rates, which are mainly caused by casual driving and a lack of understanding of the driving scene. To address this, researchers have explored the use of deep learning and computer vision techniques for the understanding of the driving scene, which involves feature extraction, classification, detection, and tracking.

Autonomous vehicles or self-driving cars are being heavily researched and developed by various technological firms and universities. The goal is to create safe and convenient navigation through the use of artificial intelligence and computer vision techniques. However, the challenges in object detection and recognition, especially in varying lighting and weather conditions, still need to be overcome. The use of deep learning and computer vision in understanding the driving scene is one of the ways to address these

challenges. The detection of road conditions, such as potholes, is also an important aspect for autonomous vehicle systems. Deep learning with computer vision has the potential to provide affordable and robust solutions for autonomous driving. One example of this is the use of a deep learning-based solution for Potholes detection in self-driving cars, which outperforms traditional image processing methods.

The detection of road conditions, such as potholes, is also a crucial aspect of an AVS. Various approaches have been taken to detect potholes, including the use of thermal cameras and optical cameras. The existing methods, however, have limited performance and are either expensive or complex. A simpler and low-cost vision-based Deep Learning model has been proposed to improve the performance of pothole detection for AVS and demonstrate its driving intelligence in avoiding potholes to prevent accidents. However, the intelligence of the AVS in making decisions based on the detected potholes remains to be explored. Alhaji et al. (2022) and Oyekanmi and Ejem (2022) have highlighted the prevalence of extensive potholes and depressions on roads, particularly in certain regions of the country, exacerbating traffic challenges.

The integration of deep learning and computer vision has the potential to provide affordable and robust solutions for the autonomous driving industry. The use of Convolutional Neural Networks (CNNs) has significantly improved the accuracy of image classification compared to previous methods using hand-crafted feature extractors and classifiers, by training high-capacity models with only a small amount of annotated detection data, CNNs provide better object detection performance than systems based on simpler features. In the case of Potholes detection in self-driving cars, a deep learning-based solution has been presented that reliably detects and recognizes Potholes, outperforming traditional image processing methods. The use of light weight deep learning techniques such as Lightweight Faster R-CNN performs faster than other techniques (Gayathri & Thangavelu, 2021).

The use of autonomous cars for Pothole detection is still in its early stages. While the technology for autonomous vehicles has advanced significantly, the infrastructure, road conditions, and regulations are still in need of improvement to make the use of autonomous cars a reality. Implementing autonomous vehicles will require investment in road upgrades, technology adaptation, and the development of clear regulations for autonomous driving. It may take some time for the technology to be widely adopted, but the benefits of increased safety, efficiency, and reduced human error in driving are likely to drive the implementation of autonomous cars in the country.

2. Related Works

In recent years, Computer Vision-based Approaches for road pothole detection involve using vehicle-mounted cameras and applying image processing techniques such as edge detection, blob analysis, and deep learning algorithms. These approaches offer flexibility and robustness in varied road and lighting conditions. Classical 2-D image processing, a traditional technique, is widely used in pothole detection, but it faces limitations in handling real-world complexities, sensitivity to image quality, and requires additional techniques for improved performance. Ma et al. (2022) applied a computer vision for

road imaging and pothole detection: a state-of-the-art review of systems and algorithms. 2-D image processing, the limitations include sensitivity to image quality and difficulty in handling occlusions and viewpoint changes. Additionally, these methods are often limited in their ability to handle variability in image conditions such as illumination changes, camera distortions, and background clutter. Classical 2-D image processing for pothole detection has limitations in dealing with real-world complexities, sensitivity to image quality, need for manual feature extraction, limited generalization, and requirement of additional techniques to improve performance.

Sensor-based Approaches for road pothole detection utilize smart sensors and actuators in vehicles and infrastructure, gathering data to enhance automated driving. These approaches rely on on-board sensors like LiDAR, radar, cameras, and external sensors to perceive surroundings. Sensors such as LIDAR and radar are employed to detect and identify potholes, providing accurate results. These sensors are expensive and require advanced sensor setups compared to computer vision-based methods.
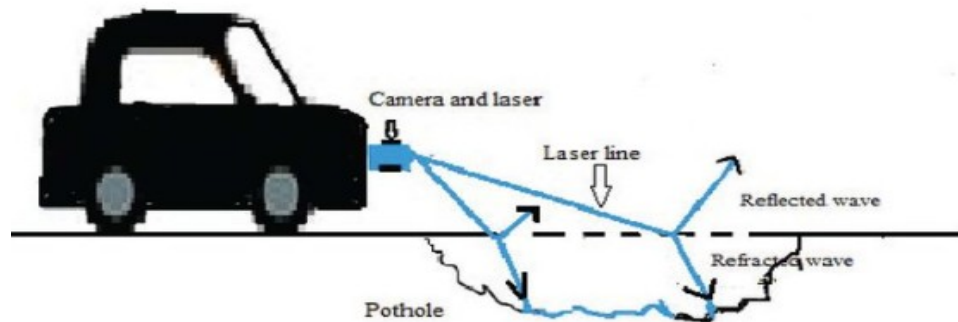

Figure 1: Camera and Laser sensor for pothole detection on an autonomous car (Source: Vupparaboina et al. , 2015)

Bosi et al. (2019) proposed the use of the Virtual Sensor Concept for Pothole Detection in Vehicle of things. The Virtual Sensor was used for pothole detection in autonomous vehicles to inform the car about road conditions, improving navigation and potentially providing road maintenance information.

Raja et al. (2022) demonstrated the development of a smart pothole-avoidance strategy for autonomous vehicles. According to the study, the model showed remarkable results in navigating potholes, which suggests its potential effectiveness in improving the safety and reliability of autonomous vehicles.

The Virtual Sensor Concept for Pothole Detection faces challenges, including the need for accurate sensor data, real-time processing, reliable communication, and limitations in certain environments. Issues such as poor sensor data quality, computational power constraints, disrupted communication, and difficulty in adverse weather conditions may impact accuracy, limiting its effectiveness and necessitating additional solutions for these challenges.

Deep Convolutional Neural Networks (DCNNs) have become a popular approach for road pothole detection due to recent advancements in machine/deep learning. There are three main types of DCNNs used for this task: image classification networks, object detection networks, and semantic segmentation networks.

Image classification networks are trained to classify road images as positive (pothole) or negative (non-pothole). Object detection networks are trained to detect road potholes at the instance level. Semantic segmentation networks are trained to segment road images into pixel-level or semantic-level representations for road pothole detection.

These networks are trained using back-propagation with a large amount of human-annotated road data. Data-driven Road pothole detection is a popular and effective approach because it does not rely on explicit parameters for road image or point cloud segmentation.

Before deep learning technology exploded, researchers typically used classical image processing algorithms to generate hand-crafted visual features and trained a Deep learning model to classify road image patches. The most representative is the CNN based models.

Ahmed (2021) developed a Smart pothole detection using deep learning based on dilated convolution. The Smart pothole detection using deep learning based on dilated convolution has the potential to provide accurate and robust road pothole detection, but also has limitations in terms of scalability and dependence on training data quality and computational cost.

Kharel and Ahmed (2021) studied the use of Inverse Perspective Mapping and CNNs for real-time potholes detection and area estimation using image processing. The study showed that while CNNs can detect potholes with adequate accuracy, they have drawbacks including the need for large amounts of labelled training data and computational requirements, as well as variability in pothole appearance which affects accuracy. To overcome these challenges, additional techniques such as data augmentation and transfer learning are required.

Yik et al. (2021) proposed a real-time pothole detection based on deep learning approach. The deep learning detection with YOLOv3 algorithm was used. The real-time pothole detection based on deep learning approach has the potential to provide real-time and accurate road pothole detection, but also has limitations in terms of scalability and dependence on training data quality and image quality.

Dutta and Chakraborty (2020) used a novel Convolutional neural network-based model for an all-terrain driving autonomous car. Convolutional Neural Network Model has the potential to provide a solution for autonomous driving in all terrains, it also has limitations in terms of robustness, dependence on training data, generalizability, and complexity.

Feng et al. (2022) applied a Segmentation of Road Potholes with Multimodal Attention Fusion Network for Autonomous Vehicles. Segmentation of Road Potholes with Multimodal Attention Fusion Network has the potential to provide accurate, robust and allows for the representation of multiple features from different modalities, leading to a

more complete representation of the road surface. Road pothole detection, but also has limitations in terms of scalability and dependence on training data quality and computational cost.

Gupta and Dixit (2022) used a hybrid of FactorNet into Faster R-CNN for potholes detection for autonomous cars. Hybrid FactorNet into Faster R-CNN for Pothole Detection has the potential to provide accurate and efficient road pothole detection, but also has limitations in terms of complexity, increased computational cost, and dependence on training data.

Kortmann et al. (2022) designed a pothole detection in an end-to-end system for autonomous driving using low-cost pre-installed sensors for real-time road damage and damage severity detection as well as cloud- and crowd-based HD Feature Maps and light weight deep learning technique. End-to-End System has the potential to provide real-time and accurate road pothole detection, but also has limitations in terms of scalability, dependence on sensor quality, and reliance on crowd-sourced data.

Ma et al. (2022) employed classical 2-D image processing-based and 3-D point cloud modelling and convolutional neural networks (CNNs). The hybrid approach of combining classical 2D image processing and 3D point cloud modeling with Convolutional Neural Networks (CNNs) offers advantages such as improved accuracy and robustness, but also presents challenges like increased complexity and computational cost, as well as higher data requirements. The use of a hybrid approach has the potential to improve road pothole detection but may also require more resources and expertise.

Manalo et al. (2022) proposed a Transfer Learning-Based System of Pothole Detection in Roads through Deep Convolutional Neural Networks. The Transfer Learning-Based System of Pothole Detection has strengths in terms of improved accuracy, efficient training, and robustness. However, it also has limitations in terms of dependence on pre-trained models, limited adaptation, and complexity.

The limitations of deep learning in autonomous car pothole detection encompass issues like data quality dependence, overfitting, computational complexity, privacy concerns, challenges with unstructured data, and limited model generalization. Chen et al. (2022) propose an effective method using EfficientNet B4 for thermal image analysis, offering lower computational complexities and high accuracy. EfficientNet architecture is recognized for its efficiency, making it suitable for resource-constrained platforms. Utilizing it as the backbone for Lightweight Faster R-CNN in pothole recognition promises high accuracy and efficiency. achieving lightweight and efficient neural networks in applications like autonomous cars (Tang et al.,2021; Jebamikyous, & Kashef ,2022). Current studies often lack model generalization and may exhibit bias, neglecting road conditions in developing countries. Addressing this, the study aims to create a dataset reflecting Nigerian road conditions, using it to train a Potholes Recognition model with Lightweight Faster R-CNN and EfficientNet for robust navigation.

According to Wang and Li (2022) the EfficientNet architecture is known for its high accuracy and efficiency, making it a popular choice for deployment on resource-constrained platforms such as autonomous cars. The lightweight and lower computational complexity of the EfficientNet architecture makes it well suited for use in systems with limited processing power, such as cars. By using this architecture as the

backbone network for a Lightweight Faster R-CNN network for pothole recognition, it is possible to achieve high accuracy and efficiency in real-time pothole detection for autonomous cars.

2. Materials and methodologies

In this study a Light-Weight Faster R-CNN is a type of object detection network that is used for pothole recognition in autonomous cars. It is an evolution of the Faster R-CNN network and is designed to be more computationally efficient while maintaining high accuracy. The architecture of the proposed model is shown in figure 2.
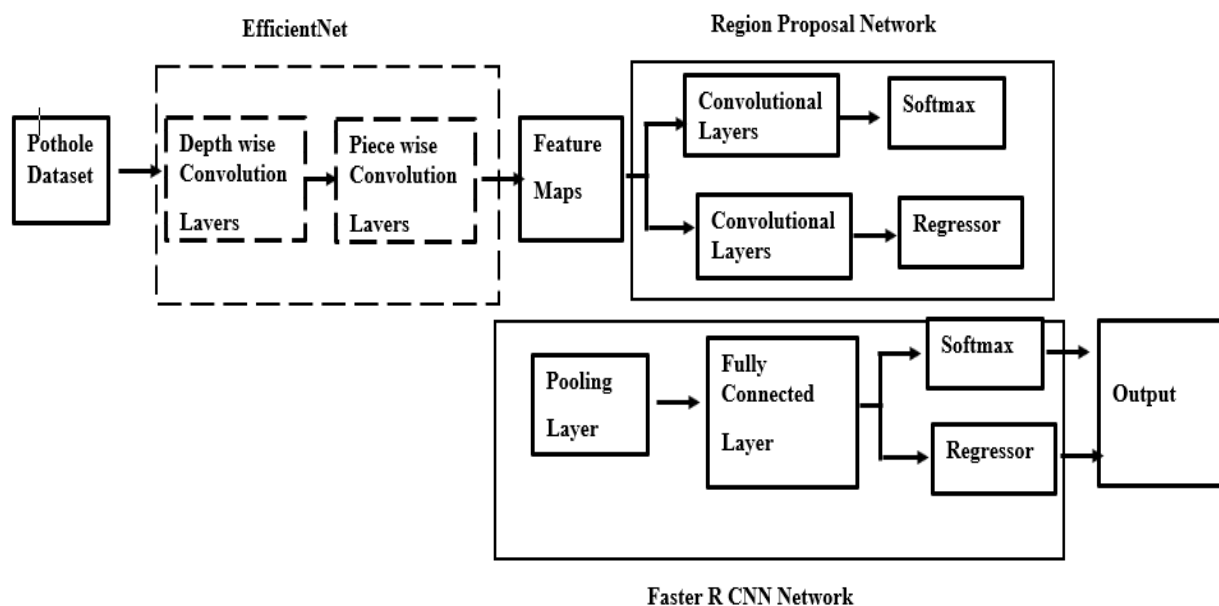

Figure 2: Proposed Light Weight Faster R-CNN model (Source: Ahmed, 2021).

The network architecture of Light-Weight Faster R-CNN consists of two main components: a backbone network and two task-specific branches. The backbone network is a convolutional neural network (CNN) that is responsible for extracting features from the input image. Commonly used backbone networks in the Light-Weight Faster R-CNN, the EfficientNet backbone network is used to generate a set of feature maps that are then fed into the two task-specific branches.

The first branch is the Region Proposal Network (RPN), which is responsible for generating proposals or candidate regions that contain objects of interest. The RPN uses anchor boxes to generate these proposals and assesses their quality using a set of binary classification scores. The proposals with the highest scores are then passed to the second branch for further processing.

The second branch is the detection branch, which is responsible for classifying the objects within the proposals generated by the RPN. The detection branch uses a set of fully connected layers to classify the objects and to generate the final bounding boxes that define their locations in the image.

The Light-Weight Faster R-CNN network is trained on a large dataset of annotated images, which includes both positive samples (images that contain potholes) and negative samples (images that do not contain potholes). The network is trained using a combination of supervised learning and reinforcement learning, where the goal is to minimize the loss function and improve the accuracy of the model.

Once the network is trained, it can be used to perform pothole recognition in real-world scenarios. During inference, the network takes an input image and generates a set of proposals and bounding boxes that define the locations of the potholes in the image. The output of the network can then be used by an autonomous vehicle to safely navigate around potholes and avoid potential damage to the vehicle.

In conclusion, the Light-Weight Faster R-CNN network is a powerful and efficient tool for pothole recognition in autonomous cars, as it combines the strengths of both CNNs and object detection algorithms to provide accurate and computationally efficient results. Using EfficientNet instead of a modified VGG16 to optimize the Faster R-Convolutional Neural Network offers advantages such as superior performance due to its ability to balance model complexity and accuracy, resulting in better efficiency and reduced computational demands, which are crucial for achieving lightweight and efficient neural networks in applications like autonomous cars (Tang et al.,2021; Jebamikyous, & Kashef ,2022).

The Potholes images will be collected by using a vehicle with cameras to snap various potholes along Kaduna metropolis. The images will be augmented with 665 potholes images from COCO datasets. A total of 800 images will be collected and used for training.

$$Precision = \frac{True\,Positive}{True\,Positive + False\,Positive} \quad ...1$$

$$Recal = \frac{True\,Positive}{True\,Positive + False\,Negative} \quad ...2$$

$$Accuracy = \frac{True\,Positive + True\,Negative}{True\,Positive + True\,Negative + False\,Positive + False\,Negative} \quad ...3$$

$$F1 = 2.\frac{Precision\,.\,Recal}{TPrecision + Recal} \quad ...4$$

3. Result

The following Faster R-CNN with VGG16, Inception V3, MobileNetV2, and ResNet50, and Improved Faster R-CNN EfficientNet were trained in this study. The goal was to assess, compare their outcomes with the proposed by evaluating them based on their parameters performance metrics. Table 1 shows the Faster R-CNN models parameters.

Table 1: The Faster R-CNN models parameters

Parameter	Value

Input Image Size:	224x224 pixels
Number of Convolutional Layers	16
Activation Function	ReLU
Anchor Box Sizes:	[32, 64, 128]
Pooling Size	7x7
Hidden Layer Unit	256
Number of Output Classes:	2
Learning Rate:	0.001
Batch Size:	16
Number of Epochs:	50
RPN Loss:	Binary Cross-Entropy
Classification Loss:	Categorical Cross-Entropy
Regression Loss:	Smooth L1 Loss

Table 1 outlines the key parameters for configuring a neural network model, including details such as the input image size (224x224 pixels), the number of convolutional layers (16), activation function (ReLU), anchor box sizes and ratios for the Region Proposal Network (RPN), RPN stride, pooling size, hidden layer units (256), the number of output classes (2), learning rate (0.001), batch size (16), and the number of epochs (50), along with the associated loss functions (Binary Cross-Entropy, Categorical Cross-Entropy, and Smooth L1 Loss).

The performance of the Improved Faster R-CNN with EfficientNet model is shown in Table 2. The table presents the results and evaluation metrics of the Improved Faster R-CNN with EfficientNet model.

Table 2: Performance results of Faster R-CNN with EfficientNet model

Description	Improved Faster R-CNN with EfficientNet
Accuracy	97.7
Precision	92.1
Recall	90.56
F1 Score	91.32

Table 2 presented performance metrics for the Improved Faster R-CNN with EfficientNet. The model achieved a notable Accuracy of 97.7%, showcasing its correctness in identifying both potholes and non-potholes, ensuring highly reliable detection. The Precision of 90.1% underscored the accuracy in identifying potholes, minimizing false positives and avoiding unnecessary interventions for non-pothole areas. The Recall of 89.56% highlighted the model's capability to capture a significant portion of

actual potholes, reducing missed detections (false negatives). The high recall ensured comprehensive pothole detection. The F1 Score of 89.83% provided a balanced assessment, indicating effective harmony between accurate pothole identification and minimized false classifications.

The Improved Faster R-CNN with EfficientNet exhibited outstanding performance in pothole detection, making it suitable for real-time applications on roads with potholes, particularly in third-world countries. The model's high accuracy, precision, recall, and F1 Score collectively contribute to its effectiveness in identifying and addressing potholes.

Table 3 shows the Summary of the classification parameters obtained after simulations of the four models. The classification performance metric used were shown for each model in Table 4.8.

Table 3: Model Comparison

Description	VGG16	Inception V3	MobileNetV2	RestNet50	Improved Faster R-CNN with EfficientNet
Accuracy	95.22	94.12	95.62	94.71	97.7
Precision	89.41	85.5	90.32	90.62	90.1
Recall	87.50	83.70	89.60	87.21	89.56
F1 Score	88.44	84.59	89.96	88.88	89.83

Table 3 presents the performance of various models in pothole detection. The VGG16 model demonstrates high accuracy, precision, and recall, indicating reliable detection, albeit with slightly lower performance compared to EfficientNet. Inception V3 exhibits good accuracy but lower precision and recall, resulting in moderate overall performance. MobileNetV2 achieves a balanced performance across accuracy, precision, and recall, slightly lower than EfficientNet. RestNet50 also maintains a balanced performance but with slightly lower accuracy and precision compared to EfficientNet.

The Improved Faster R-CNN with EfficientNet outshines all other models, boasting the highest accuracy (97.7%), precision (90.1%), recall (89.56%), and F1 Score (89.83%). Considering these superior metrics, it emerges as the best model for real-time pothole detection. Despite potential overfitting concerns, this model showcases exceptional performance compared to other architectures. The choice of the best model depends on specific application requirements and the tolerance for false positives and false negatives.

4. Conclusion

This paper focused on advancing pothole detection systems by implementing the improved Faster R-CNN with EfficientNet algorithm. Beginning with a thorough review of pothole detection systems, the study aimed to address the challenges in this domain. The proposed algorithm, leveraging Faster R-CNN and EfficientNet, demonstrated significant advancements in accuracy, computational complexity reduction, and overall efficiency for real-world applications. The research methodology covered systematic data collection, model development, and rigorous evaluation. The developed Potholes Recognition model, integrating EfficientNet with Faster R-CNN, underwent

comprehensive evaluation against benchmarks, showcasing impressive accuracy and precision metrics.
The findings underscore the model's efficacy with Accuracy of 97.7%, Precision of 92.1%, Recall of 90.56%, and F1 Score of 91.32%. This success contributes substantially to pothole detection technology, offering a practical and efficient solution for real-world applications and paving the way for further advancements.

Future research opportunities include advancing neural network architectures, incorporating multimodal data, real-world deployment, dynamic pothole classification, transfer learning, autonomous vehicle integration, user feedback utilization, energy-efficient implementations, privacy considerations, and international collaboration. These directions aim to enhance pothole detection systems globally, contributing to safer and well-maintained road infrastructures.

Reference

Ahmed, K. R. (2021). Smart pothole detection using deep learning based on dilated convolution. *Sensors*, *21*(24), 8406. https://doi.org/10.3390/s21248406

Alhaji, M. M., Alhassan, M., Adejumo, T. W., & Abdulkadir, H. (2022). Road pavement collapse from overloaded trucks due to traffic diversion: A case study of minna-kateregi-Bida road. *Nigeria. Engineering Failure Analysis*, 131, 105829. https://doi.org/10.1016/j.engfailanal.2021.105829

Bosi, I., Ferrera, E., Brevi, D., & Pastrone, C. (2019). In-vehicle IoT platform enabling the virtual sensor concept: A pothole detection use-case for cooperative safety. *Proceedings of the 4th International Conference on Internet of Things, Big Data and Security*, 1-6. https://doi.org/10.5220/0007690602320240

Chen, C., Chandra, S., Han, Y., & Seo, H. (2022). Deep learning-based thermal image analysis for pavement defect detection and classification considering complex pavement conditions. *Remote Sensing*, *14*(1), 106. https://doi.org/10.3390/rs14010106

Dutta, D., & Chakraborty, D. (2020). A novel Convolutional neural network based model for an all terrain driving autonomous car. *2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN)*, 1-6. https://doi.org/10.1109/icacccn51052.2020.9362818

Feng, Z., Guo, Y., Liang, Q., Bhutta, M. U., Wang, H., Liu, M., & Sun, Y. (2022). MAFNet: Segmentation of road potholes with multimodal attention fusion network for autonomous vehicles. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-12. https://doi.org/10.1109/tim.2022.3200100

Gayathri, K., & Thangavelu, S. (2021). Novel deep learning model for vehicle and pothole detection. *Indonesian Journal of Electrical Engineering and Computer Science*, *23*(3), 1576. https://doi.org/10.11591/ijeecs.v23.i3.pp1576-1582

Gupta, P., & Dixit, M. (2022). Image-based road pothole detection using deep learning model. *2022 14th International Conference on Computational Intelligence and Communication Networks (CICN)*, 1-6. https://doi.org/10.1109/cicn56167.2022.10008278

Jebamikyous, H. H., & Kashef, R. (2022). Autonomous vehicles perception (avp) using deep learning: Modeling, assessment, and challenges. *IEEE Acces*s, 10, 10523-10535.

Kharel, S., & Ahmed, K. R. (2021). Potholes detection using deep learning and area estimation using image processing. *Lecture Notes in Networks and Systems*, 373-388. https://doi.org/10.1007/978-3-030-82199-9_24

Kok, M., Ren, H., Han, J., & Hu, B. (2021). Object detection and classification for pothole detection with autonomous vehicles: a review. *IEEE Access*, 9, 113483-113499. https://doi.org/10.1109/ACCESS.2021.3097116

Kortmann, F., Fassmeyer, P., Funk, B., & Drews, P. (2022). Watch out, pothole! featuring road damage detection in an end-to-end system for autonomous driving. *Data & Knowledge Engineering*, *142*, 102091. https://doi.org/10.1016/j.datak.2022.102091

Ma, N., Fan, J., Wang, W., Wu, J., Jiang, Y., Xie, L., & Fan, R. (2022). Computer vision for road imaging and pothole detection: A state-of-the-art review of systems and algorithms. *Transportation Safety and Environment*, *4*(4), 1-5. https://doi.org/10.1093/tse/tdac026

Manalo, J. M., Alon, A. S., Austria, Y. D., Merencilla, N. E., Misola, M. A., & Sandil, R. C. (2022). A transfer learning-based system of pothole detection in roads through deep Convolutional neural networks. *2022 International Conference on Decision Aid Sciences and Applications (DASA)*. https://doi.org/10.1109/dasa54658.2022.9765227

Oyekanmi, O. J., & Ejem, E. A. (2022). Load damaging effects of overloaded trucks on federal highway pavement structures in Nigeria. *Research Developments in Science and Technology* , 5, 140-156. https://doi.org/10.9734/bpi/rdst/v5/2186b

Oyinbo, A. M., H. Bello-Salau, H., Mohammed S., Zubair, S., Adejo, A., & Abdulkarim, H. T. (2020). Towards an Improved Potholes Anomaly Detection Based on Discrete Wavelet Transform and Convolution Neural Network: A Proposal. *Nigerian Journal of Engineering*, 22(7), 86-90.

Raja, G., Anbalagan, S., Senthilkumar, S., Dev, K., & Qureshi, N. M. (2022). SPAS: Smart pothole-avoidance strategy for autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *23*(10), 19827-19836. https://doi.org/10.1109/tits.2022.3161589

Tang, H., Wang, Y., Yuan, W., & Sun, Y. (2021). *An Efficientnet Based Method for Autonomous Vehicles Trajectory Prediction.* In 2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI) (pp. 18-21). IEEE.

Wang, C., & Li, Y. (2022). Motion prediction for autonomous vehicles based on EfficientNet-B1. *2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE)*, 1-6. https://doi.org/10.1109/cisce55963.2022.9851007

Yik, Y. K., Alias, N. E., Yusof, Y., & Isaak, S. (2021). A real-time pothole detection based on deep learning approach. *Journal of Physics: Conference Series*, *1828*(1), 012001. https://doi.org/10.1088/1742-6596/1828/1/012001